Data mining Toronto Fire Incidents Final Report

Abstract

The objective of this project is to build predictors to estimate the financial impact of fire incidents, using open fire incident data from the city of Toronto. By analysing factors including, but not limited to, the extent of fire, source of fire, ignition material and property use, we aim to provide an accurate estimation of the amount of dollar loss per fire incident. The project seeks to uncover these circumstantial factors that affect the financial impact per every fire incident in Toronto.

This project uses open soruce data published by the City of Toronto: https://open.toronto.ca/dataset/fire-incidents/

The dataset includes fire incidents as defined by the Ontario Fire Marshal (OFM) up to December 31, 2022. It contains 43 columns and nearly 30k rows.

Pipeline

At a high level, the pipeline achieves the following:

- `Pipeline`
  - `Data_Preprocessing`
    - `Data_cleaning`
      - Drops columns with no relevance.
      - Sanitizes descrepancies for manual input data.
      - Replaces empty strings in categorical columns with `pd.NA`.
      - Drops rows with no values at all according to feature: `Area_of_Origin`.
      - Removes false positives, according to feature: `Final_Incident_Type`
      - Converts non-null values of categorical columns to string to ensure data integrity, ease the imputation processs.
      - Removes outliers using z-score method to eliminate rows that 3 standard deviations from the mean, based on response feature, `Estimated_Dollar_Loss`.
      - Replaces values of `NAType` with `np.nan` for numerical columns.
    - `Feature_Engineering`
      - creates a new feature `Control_Time`. (How long fire burned for.)
      - creates a new feature called `Response_Time`. (How long took for the first arriving unit to get to the incident)
    - `feature_transformers`
      - Applies simple imputer to all categorical features.
      - Applies KNN imputer to all numerical features.
      - Applies ordinal encoding to all categorical features.
      - Standard scale all numerical features.
      - Applies log transformation on response variable.
    - `Feature Selection`
      - Drops features with low Spearman correlation coefficients to response variable.

        - Drops categorical features with low Kruskal-Wallis H-test statistic to response variable.
        - Drops categorical features with low Chi-Squared test statistic to response variable.
        - Removes 4 worst features using `SelectKBest` method with an ANOVA F-test.
    - `model(regressors)`
        - Linear models
            - Multiple Linear Regression (OLS - Ordinary Least Squares)
            - Lasso (Least Absolute Shrinkage and Selection Operator)
            - Elastic-Net
            - Huber Regressor
        - Ensemble methods
            - Random Forest Regressor
            - XGBoost Regressor
        - Non-Linear Models
            - Neural networks (MLP - Multi-layer Perceptron)

The hyperparameters of models were tuned using `GridSearchCV`.

Custom Modules Developed

- data_clean.py

  Classes:

  - `DataCleaner`:

    Functions:

    - `cleanse_dataframe(df)`: Returns a cleansed dataframe.

- data_reduction.py

  Classes:

  - `FeatureAnalysis`:

    Functions:

    - `keepStrongestFeaturesInDataFrame(responseVariable, df, p_value, correlation)`: Returns a dataframe with features that have a strong correlation and statistical significance to `responseVariable`.

Data Analysis and Visualization

See src/ExpDataAnalysis.ipynb and src/proposal/hypothesis_testing.ipynb

Data Preprocessing Pipeline

In [1]:
```
# Third Party libraries
import pandas as pd

from sklearn.compose import ColumnTransformer
```

```
from sklearn.preprocessing import OrdinalEncoder
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder, LabelEncoder
from sklearn.impute import SimpleImputer
from sklearn.impute import KNNImputer
from sklearn.neighbors import KNeighborsClassifier
import pandas as pd

from sklearn.linear_model import LinearRegression
```

In [2]:
```
# Load DF
df = pd.read_csv('../../data/raw/Fire_Incidents_Data.csv', low_memory=False)
```

In [3]:
```
# Feature Engineering before removing columns

df['Fire_Under_Control_Time'] = pd.to_datetime(df['Fire_Under_Control_Time'])
df['TFS_Alarm_Time'] = pd.to_datetime(df['TFS_Alarm_Time'])
df['TFS_Arrival_Time'] = pd.to_datetime(df['TFS_Arrival_Time'])

df['Control_Time'] = (df['Fire_Under_Control_Time'] - df['TFS_Alarm_Time']).dt.total_sec
df['Response_Time'] = (df['TFS_Arrival_Time'] - df['TFS_Alarm_Time']).dt.total_seconds()
```

Cleanse dataframe.

See modules/data_clean.py, or `Data_Cleaning` section of Pipeline Objectives for more details.

In [4]:
```
# Import custom Data_cleaning module
from modules.data_clean import DataCleaner

# Cleanse Dataframe
df = DataCleaner.cleanse_dataframe(df)
```

Defining all features.

- Numerical Columns
- Categorial Columns
  - Ordinal Columns
  - Onehot Columns

In [5]:
```
NUMERICAL_COLS = [
    "Civilian_Casualties",
    "Count_of_Persons_Rescued",
    "Estimated_Dollar_Loss",
    "Estimated_Number_Of_Persons_Displaced",
    "Number_of_responding_apparatus",
    "Number_of_responding_personnel",
    "TFS_Firefighter_Casualties",
    "Control_Time",
    "Response_Time"
]

CATEGORICAL_COLS = ['Area_of_Origin', 'Building_Status', 'Business_Impact', 'Extent_Of_F
                'Fire_Alarm_System_Impact_on_Evacuation', 'Fire_Alarm_System_Operation',
                'Ignition_Source', 'Initial_CAD_Event_Type', 'Material_First_Ignited', '
                'Possible_Cause', 'Property_Use', 'Smoke_Alarm_at_Fire_Origin', 'Smoke_A
                'Smoke_Alarm_at_Fire_Origin_Alarm_Type', 'Smoke_Alarm_Impact_on_Persons_
                'Smoke_Spread', 'Sprinkler_System_Operation', 'Sprinkler_System_Presence

# ['Business_Impact', 'Extent_Of_Fire', 'Sprinkler_System_Presence', 'Status_of_Fire_On_
ORDINAL_COLS = CATEGORICAL_COLS[2:4] + CATEGORICAL_COLS[20:22]
```

```
# Everything else.
ONEHOT_COLS = list(set(CATEGORICAL_COLS) - set(ORDINAL_COLS))
```

Imputation

Categorical Imputation

A SimpleImputer is applied to all `CATEGORICAL_COLS`, as it can work with string data types.

In [6]:
```
# Specify pd.NA as the missing value indicator for SimpleImputer
import numpy as np

imputer = SimpleImputer(strategy='most_frequent', missing_values=pd.NA)

# Apply the imputer to the categorical columns
df[CATEGORICAL_COLS] = imputer.fit_transform(df[CATEGORICAL_COLS])
```

Numerical imputation.

A KNN imputer is applied to all `NUMERICAL_COLS` missing data.

In [7]:
```
import numpy as np

# Replace pd.NA with np.nan
# KNNImputer does not directly support pd.NA
df = df.replace(pd.NA, np.nan)

imputer = KNNImputer()

# Apply the imputer to the categorical columns
df[NUMERICAL_COLS] = imputer.fit_transform(df[NUMERICAL_COLS])
```

Categorical Encoding

This will encode all `CATEGORICAL_COLS`.

In [8]:
```
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder
import numpy as np

# Specify ordinal encoder
ordinal_encoder = OrdinalEncoder(handle_unknown="use_encoded_value", unknown_value=np.na

# Apply the encoder to specified columns
df[CATEGORICAL_COLS] = ordinal_encoder.fit_transform(df[CATEGORICAL_COLS])
```

Standard scaler on numerical Data

Apply standard scaling to all `NUMERICAL_COLS`. Standardizes features by removing the mean and scaling to unit variance to create a normal distribution. Many models may assume normally distributed data.

In [9]:
```
from sklearn.preprocessing import StandardScaler

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the DataFrame
df[NUMERICAL_COLS] = scaler.fit_transform(df[NUMERICAL_COLS])
```

Log transform response variable.

Log transform the `responseVariable`, to improve heteroskedasticity (make the residual variance appear more constant) and normality (reduce the skewness of the data).

In [10]:
```
# Log transform the Estimated_Dollar_Loss column
df['Estimated_Dollar_Loss'] = np.log(df['Estimated_Dollar_Loss'] + 1)  # Adding 1 to avo
```

Feature Selection (Part 1)

Select features based on the following:

- Spearman correlation coefficients with p-values for each categorical feature.
- Kruskal-Wallis H-test statistic for each categorical feature
- Calculate Chi-Squared test statistic for each categorical feature

Using these values, a measure of `p-value` and `correlation` is developed for each column against the response variable.

Columns are kept so long as its `(['P-value'] < 0.1) & (['Correlation'] > 0.003)`.

This will drop the following features: {'Final_Incident_Type', 'Smoke_Alarm_at_Fire_Origin'}. Increasing the correlation threshold any more will drop more features and will result in a worse r-sq.

In [11]:
```
# Import Data_reduction module
from modules.data_reduction import FeatureAnalysis

# helper function that will drop low correlated variables in the dataset
df_reduced = FeatureAnalysis.keepStrongestFeaturesInDataFrame('Estimated_Dollar_Loss', d
```

Train test split

In [12]:
```
from sklearn.model_selection import train_test_split
df = df_reduced
# List all columns in the DataFrame
all_columns = df.columns.tolist()

# Use every other column in the df except for the response variable
features = [col for col in all_columns if col != 'Estimated_Dollar_Loss']

# Separate features from response variable
X, y = df[features], df['Estimated_Dollar_Loss']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=1
```

Feature Selection (Part 2)

Perform feature selection using the SelectKBest method from with an ANOVA F-test (f_classif). It then removes the worst four features from both the training and testing sets.

In [13]:
```
from sklearn.feature_selection import SelectKBest, f_classif

# Perform feature selection using SelectKBest with ANOVA F-test
k_best_features = SelectKBest(score_func=f_classif, k=X_train.shape[1]) # Select all fea
```

```
X_train_selected = k_best_features.fit_transform(X_train, y_train)

# Get the scores and indices of the features
feature_scores = k_best_features.scores_

# Get a list of indexes based on the value of the index's element. Sorted.
# The list of indexes is generated by the range function. (len(feature_scores))
feature_indices = sorted(range(len(feature_scores)), key=lambda i: feature_scores[i], re

# Identify the worst four features to remove
features_to_remove = [feature_indices[-1], feature_indices[-2], feature_indices[-3], fea

# remove the worst four features from both training and testing sets
X_train = X_train.drop(X_train.columns[features_to_remove], axis=1)
X_test = X_test.drop(X_test.columns[features_to_remove], axis=1)
```

Modelling Implementation and Evaluation

Helper Functions

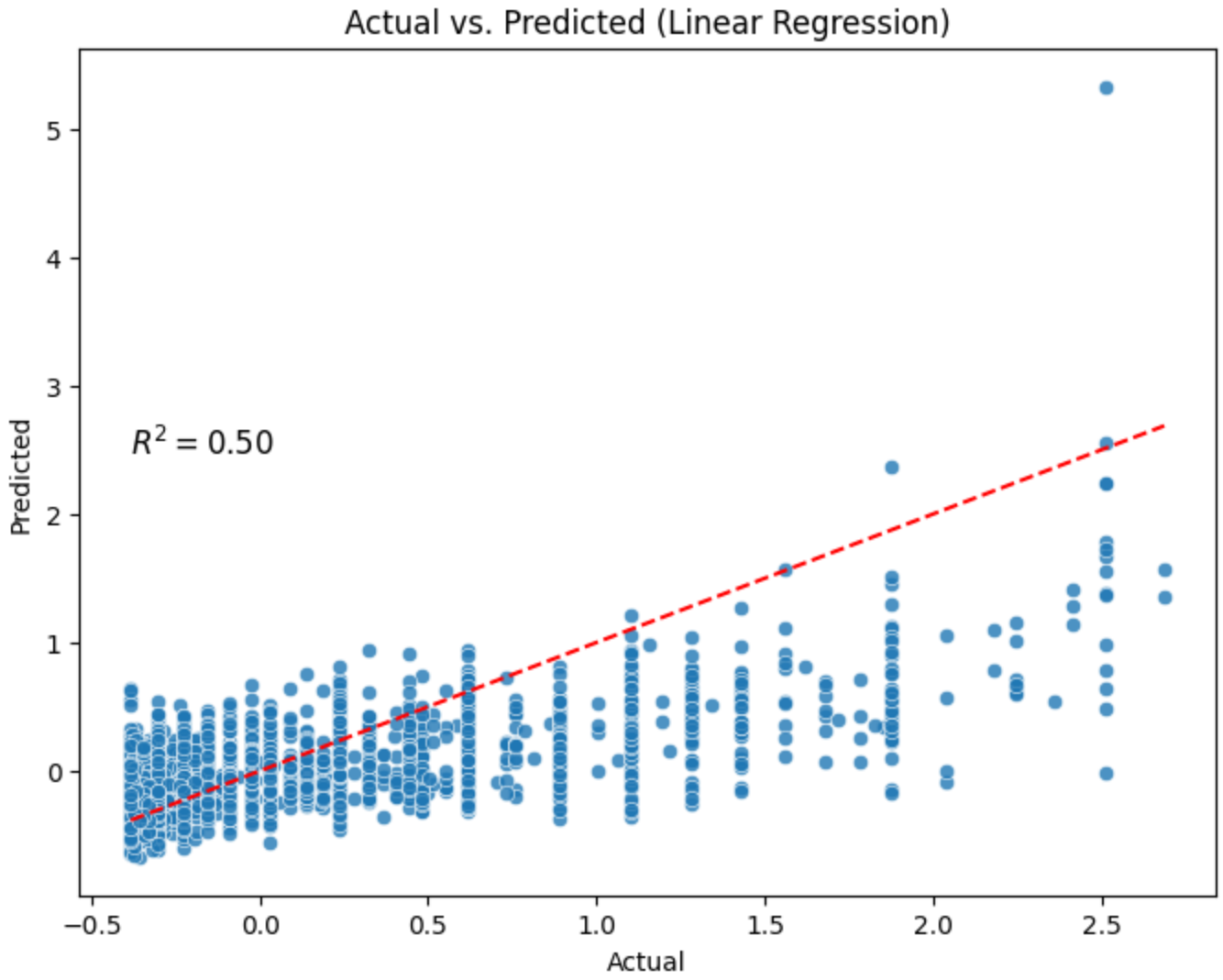
In [14]:
```
# Function: Print Results of a Model (R2, MEAN ABSOLUTE ERROR, MEAN SQUARED ERROR, COEF
def print_results(r2, mae, mse, coefficients, intercept):
    print(f"R-squared score: {r2:.4f}")
    print(f"Mean Absolute Error: {mae}")
    print(f"Mean Squared Error: {mse}")
    print(f"Coefficients: {coefficients}")
    print(f"Intercept: {intercept}")

# Function: Return Results (R2, MEAN ABSOLUTE ERROR, MEAN SQUARED ERROR, COEF and INTERC
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
def get_results(model, y_test, y_pred):
    r2 = r2_score(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    coefficients = model.coef_
    intercept = model.intercept_
    return (r2, mae, mse, coefficients, intercept)

# Function: Plot Scatter plot for regression model. (y_pred = lr.predict(X_test), R2 Sco
import matplotlib.pyplot as plt
import seaborn as sns
def plotRegression(y_pred, r2, modelName=None):
    # Scatter plot with regression line
    plt.figure(figsize=(8, 6))
    sns.scatterplot(x=y_test, y=y_pred, alpha=0.8)
    plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], linestyle='--',
    plt.title(f'Actual vs. Predicted ({modelName})')
    plt.xlabel('Actual')
    plt.ylabel('Predicted')

    # Annotate plot with R-squared value
    plt.text(y_test.min(), y_test.max(), f'$R^2 = {r2:.2f}$', fontsize=12, verticalalign

    plt.show()
```

Linear Regression

In [15]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

lr = LinearRegression() # to do - settings hyperparameters
lr.fit(X_train, y_train)

y_pred_lr = lr.predict(X_test)
residuals_lr = y_test - y_pred_lr

(r2_lr, mae_lr, mse_lr, coefficients_lr, intercept_lr) = get_results(lr, y_test, y_pred_

# Results - Another option would be to use statsmodels to display a summary
print("---------MLR----------")
print_results(r2_lr, mae_lr, mse_lr, coefficients_lr, intercept_lr)
plotRegression(y_pred_lr, r2_lr, 'Linear Regression')
print("----------------------")
```

```
---------MLR----------
R-squared score: 0.5005
Mean Absolute Error: 0.18855416108801634
Mean Squared Error: 0.09082654811349444
Coefficients: [-6.03237515e-04  9.07617670e-03  2.20463029e-02  4.03249487e-03
  2.95734300e-02  3.52263677e-02  5.40422886e-03  2.63843115e-03
  1.43456053e-02 -5.32225358e-05  1.63343605e-03 -1.87189687e-02
 -1.40112864e-01  3.27864841e-01  1.83400740e-03  1.98049938e-04
  1.03167919e-02  2.07188823e-03 -2.73848219e-03  3.44884662e-03
  1.31544149e-03 -1.82642147e-02  3.15689721e-02  2.08844500e-02
  2.22179295e-02]
Intercept: -0.517010116248453
```



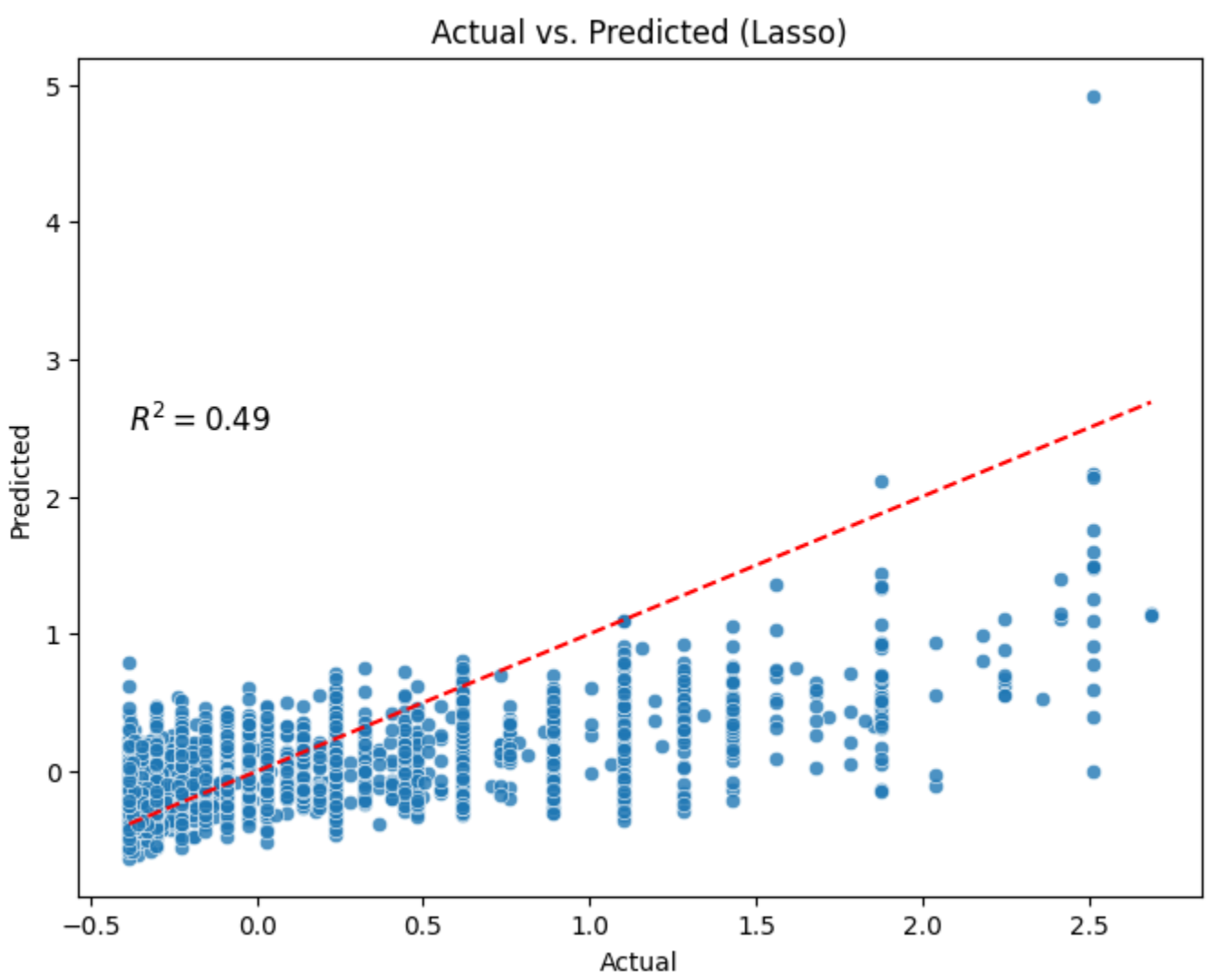

```
----------------------
```

Lasso Regression

In [16]:

```
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV

# Need to scale before using Lasso. I am not sure if we've already done in preprocessing
# from sklearn.preprocessing import StandardScaler
# scaler = StandardScaler()
# X_train = scaler.fit_transform(X_train)
# X_test = scaler.fit_transform(X_test)

# Lasso Model 1 = basic

lasso = Lasso(tol=0.05)
lasso.fit(X_train, y_train)
y_pred_lasso = lasso.predict(X_test)
(r2_lasso, mae_lasso, mse_lasso, coefficients_lasso, intercept_lasso) = get_results(lass

print("---------LASSO----------")
print_results(r2_lasso, mae_lasso, mse_lasso, coefficients_lasso, intercept_lasso)
print("------------------------")

# Lasso Model 2 = Testing different parameters (CROSS-VALIDATOR: CV)

param_grid = {
        'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
}

lasso_cv = GridSearchCV(lasso, param_grid, cv=3, n_jobs=-1)
lasso_cv.fit(X_train, y_train)

# Get the Lasso with the best estimators
lasso_best = lasso_cv.best_estimator_
y_pred_lasso_best = lasso_best.predict(X_test)
(r2_lasso_best, mae_lasso_best, mse_lasso_best, coefficients_lasso_best, intercept_lasso

print("---------LASSO CV BEST----------")
print_results(r2_lasso_best, mae_lasso_best, mse_lasso_best, coefficients_lasso_best, in
plotRegression(y_pred_lasso_best, r2_lasso_best, 'Lasso')
print("--------------------------")
```

```
---------LASSO----------
R-squared score: 0.0050
Mean Absolute Error: 0.27546187522614746
Mean Squared Error: 0.18093335069258049
Coefficients: [ 0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.         -0.
  0.          0.          0.         -0.00015448  0.          0.
  0.          0.          0.          0.          0.          0.
  0.        ]
Intercept: -0.12569878120827602
------------------------
---------LASSO CV BEST----------
R-squared score: 0.4902
Mean Absolute Error: 0.1870998903408478
Mean Squared Error: 0.09271636404302167
Coefficients: [-4.43928675e-04  8.10169938e-03  9.28989271e-03  0.00000000e+00
  2.24547034e-02  3.58710302e-02  3.47166606e-03  0.00000000e+00
  4.34747804e-03 -2.58207933e-05  1.67300008e-03 -1.14196740e-02
  1.55946271e-01  3.16098038e-02  2.21873756e-03  1.54448249e-04
  8.77290506e-03  0.00000000e+00  0.00000000e+00  3.04083041e-03
 -0.00000000e+00 -0.00000000e+00  3.03908328e-02  1.38122884e-02
  1.34876372e-02]
Intercept: -0.5237731159897542
```



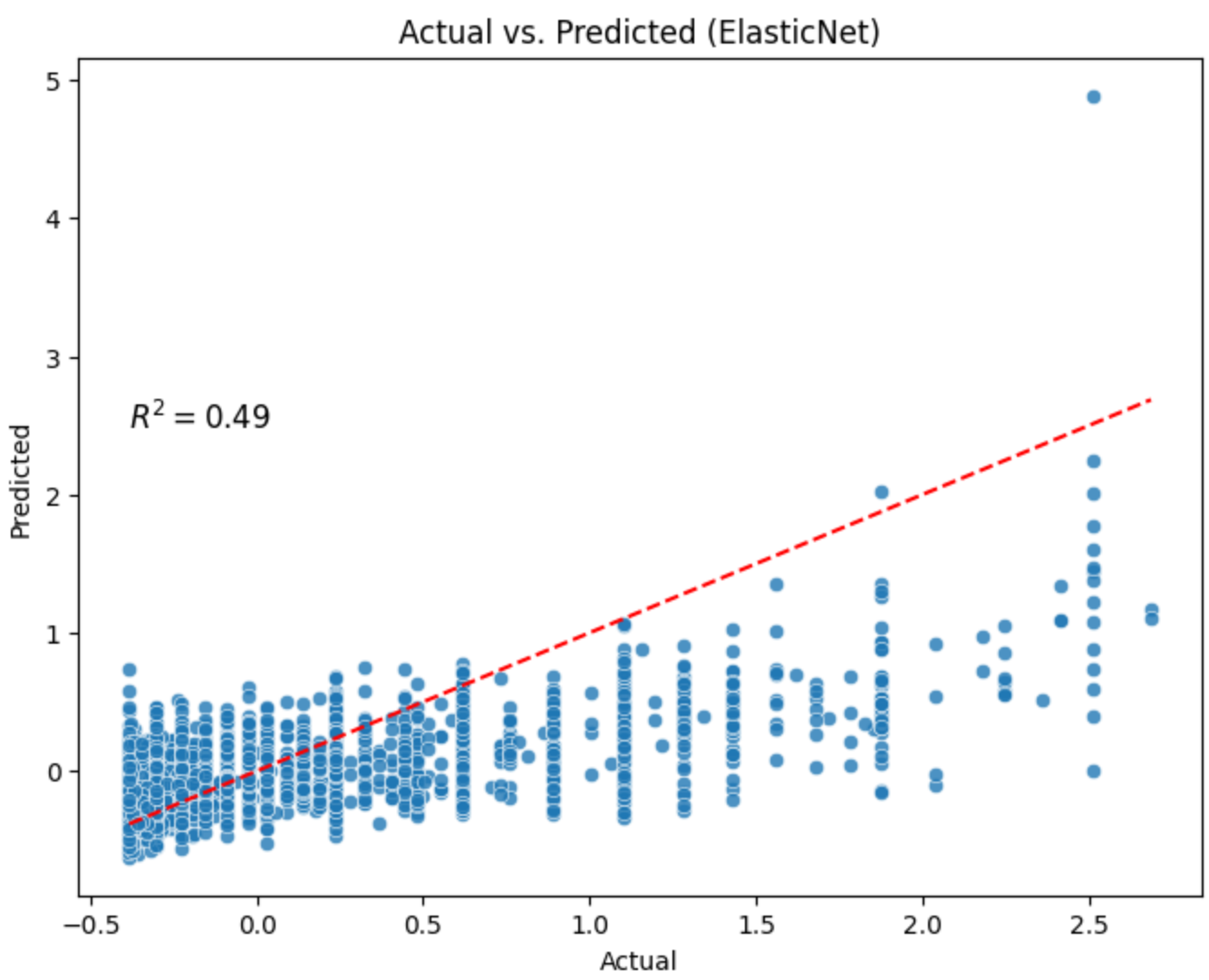
ElasticNet

In [17]:

```
from sklearn.linear_model import ElasticNet

# X_train and X_test should be scaled

# ElasticNet Model 1 = basic

elastic_net = ElasticNet()
elastic_net.fit(X_train, y_train)

y_pred_elastic_net = elastic_net.predict(X_test)

(r2_elastic_net, mae_elastic_net, mse_elastic_net, coefficients_elastic_net, intercept_e

print("---------ELASTIC NET BASIC----------")
print_results(r2_elastic_net, mae_elastic_net, mse_elastic_net, coefficients_elastic_net
print("----------------------------")

# ElasticNet Model 2 = Testing different parameters (CROSS-VALIDATOR: CV)

param_grid = {
        'alpha': [0.1, 0.3, 0.5, 0.7, 0.9, 1.0],
        'l1_ratio': [0.1, 0.3, 0.5, 0.7, 0.9, 1.0],
}

elastic_cv = GridSearchCV(elastic_net, param_grid, scoring='neg_mean_squared_error', cv=
elastic_cv.fit(X_train, y_train)
```

```python
# Get the Elastic with the best estimators
elastic_best = elastic_cv.best_estimator_
y_pred_elastic_best = elastic_best.predict(X_test)
(r2_elastic_best, mae_elastic_best, mse_elastic_best, coefficients_elastic_best, interce

print("---------ELASTIC BEST CV----------")
print_results(r2_elastic_best, mae_elastic_best, mse_elastic_best, coefficients_elastic_
plotRegression(y_pred_elastic_best, r2_elastic_best, 'ElasticNet')
print("---------------------------")
```

```
---------ELASTIC NET BASIC----------
R-squared score: 0.0171
Mean Absolute Error: 0.27223163393691796
Mean Squared Error: 0.1787360446760427
Coefficients: [ 0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.0002938   0.00080467 -0.
  0.          0.          0.         -0.00037746  0.          0.
  0.          0.          0.          0.          0.          0.
  0.        ]
Intercept: -0.15707875966865387
---------------------------
---------ELASTIC BEST CV----------
R-squared score: 0.4860
Mean Absolute Error: 0.18796568279373058
Mean Squared Error: 0.093463413322066
Coefficients: [-0.00048634  0.00809941  0.01017923  0.          0.02228831  0.03673514
  0.00300404  0.          0.00388058 -0.          0.00164354 -0.01265215
  0.07739217  0.09686308  0.00227374  0.00013964  0.00880723  0.
  0.          0.0034091  -0.         -0.          0.0298837   0.01514389
  0.01838877]
Intercept: -0.51930000625453
```



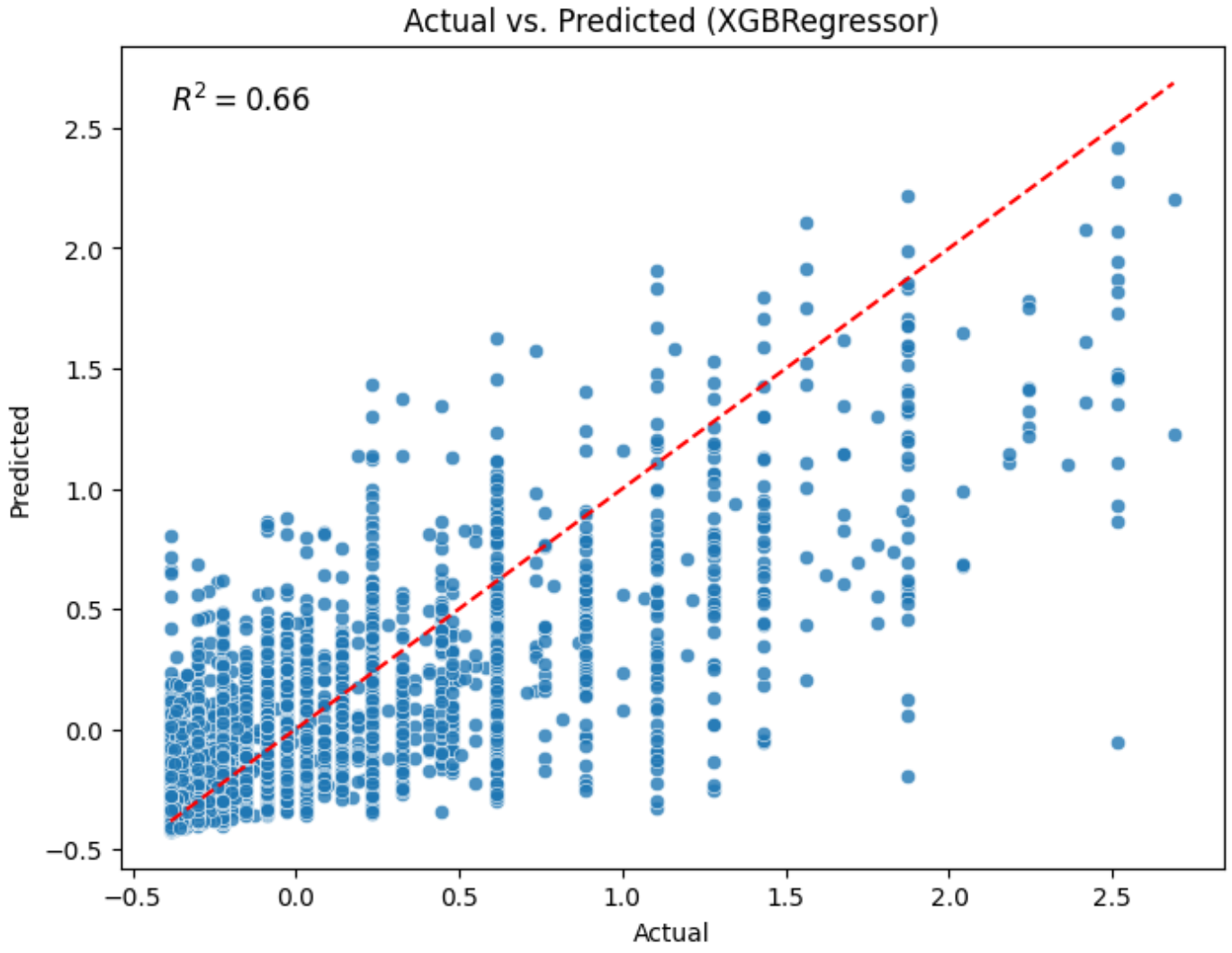
XGBRegressor

In [18]:

```
import multiprocessing
import xgboost as xgb

# Initialize XGBRegressor
xgb_model = xgb.XGBRegressor(objective='reg:squarederror',
    n_jobs=-1, tree_method="hist"
)

# XGB Hyperparamters hav been tuned using this CV param grid.
# Not including parameters 'subsample' or 'colsample_bytree' due to resource usage.
param_grid = {"max_depth": [2, 4, 6],
              "n_estimators": [50, 100, 200],
              'gamma': [0, 0.1, 0.2, 0.3, 0.4],
              'learning_rate': [0.05, 0.1, 0.2, 0.3]}

# Cross validate model. Find the best hyperparamters using the grid above
xgb_cv = GridSearchCV(
    estimator=xgb_model,
    param_grid=param_grid,
    verbose=1,
    n_jobs=2
)

# fit model
xgb_cv.fit(X_train, y_train)
```

```
# Best model parameters from GridSearchCV
print("Best parameters:", xgb_cv.best_params_)
print("Best cross-validation score: {:.2f}".format(xgb_cv.best_score_))

# Predict on the test data
xgb_y_pred = xgb_cv.predict(X_test)


xgb_r2 = r2_score(y_test, xgb_y_pred)
xgb_mae = mean_absolute_error(y_test, xgb_y_pred)
xgb_mse = mean_squared_error(y_test, xgb_y_pred)

print(f"R-squared score: {xgb_r2:.4f}")
print(f"Mean Absolute Error: {xgb_mae}")
print(f"Mean Squared Error: {xgb_mse}")
plotRegression(xgb_y_pred, xgb_r2, 'XGBRegressor')
```

```
Fitting 5 folds for each of 180 candidates, totalling 900 fits
Best parameters: {'gamma': 0.1, 'learning_rate': 0.05, 'max_depth': 4, 'n_estimators': 2
00}
Best cross-validation score: 0.63
R-squared score: 0.6583
Mean Absolute Error: 0.13951366645057664
Mean Squared Error: 0.06213834505077028
```



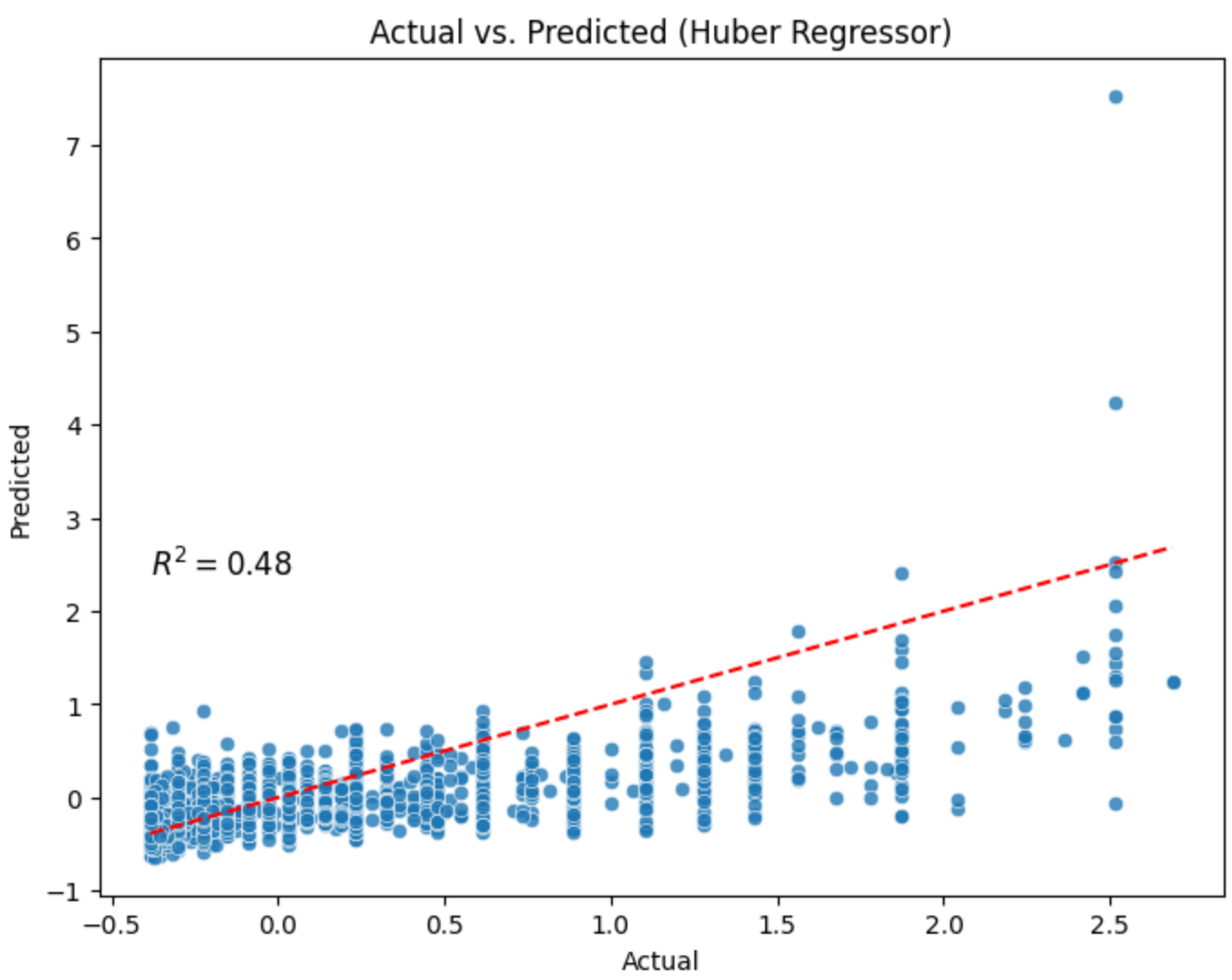
Huber Regression

In [19]:

```
from sklearn.linear_model import HuberRegressor
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import matplotlib.pyplot as plt
```

```
import seaborn as sns

# HuberRegressor Setup
huber = HuberRegressor()

# GridSearchCV
param_grid = {
    'epsilon': [1.35, 1.5, 2.0],
    'max_iter': [1000, 1500, 2000],
    'alpha': [0.0001, 0.001, 0.01, 0.1],
    'warm_start': [True, False]
}
#Best parameters: {'alpha': 0.001, 'epsilon': 2.0, 'max_iter': 1000, 'warm_start': True}
grid_search = GridSearchCV(huber, param_grid, cv=5, verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)

# Best model parameters from GridSearchCV
print("Best parameters:", grid_search.best_params_)
print("Best cross-validation score: {:.2f}".format(grid_search.best_score_))

# Using best parameters to fit Huber regressor
huber_best = grid_search.best_estimator_
huber_best.fit(X_train, y_train)
y_pred_huber = huber_best.predict(X_test)

# Store best scores
r2_huber = huber_best.score(X_test, y_test)
mae_huber = mean_absolute_error(y_test, y_pred_huber)
mse_huber = mean_squared_error(y_test, y_pred_huber)

# Get results using the helper function
print("---------HUBER REGRESSOR----------")
print_results(r2_huber, mae_huber, mse_huber, huber_best.coef_, huber_best.intercept_)
plotRegression(y_pred_huber, r2_huber, 'Huber Regressor')
print("----------------------------------")
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
Best parameters: {'alpha': 0.001, 'epsilon': 2.0, 'max_iter': 1000, 'warm_start': True}
Best cross-validation score: 0.42
---------HUBER REGRESSOR----------
R-squared score: 0.4836
Mean Absolute Error: 0.1766819337931957
Mean Squared Error: 0.0939093785400646
Coefficients: [-6.76555086e-04  5.67906376e-03  1.40373376e-02  1.25086158e-03
  2.56285232e-02  2.42557387e-02  6.73553843e-03 -2.06782757e-03
  1.03120532e-02 -1.39626342e-04  1.66388713e-03 -7.47184250e-03
  1.56728450e-01  4.85576703e-02  1.32951981e-03  2.68729738e-04
  6.15128572e-03  7.26711281e-04 -3.75400438e-03  3.14746985e-03
  2.63546216e-03 -1.27249066e-02  2.07010447e-02  2.97696797e-02
  5.83088424e-02]
Intercept: -0.4773542224065559
```



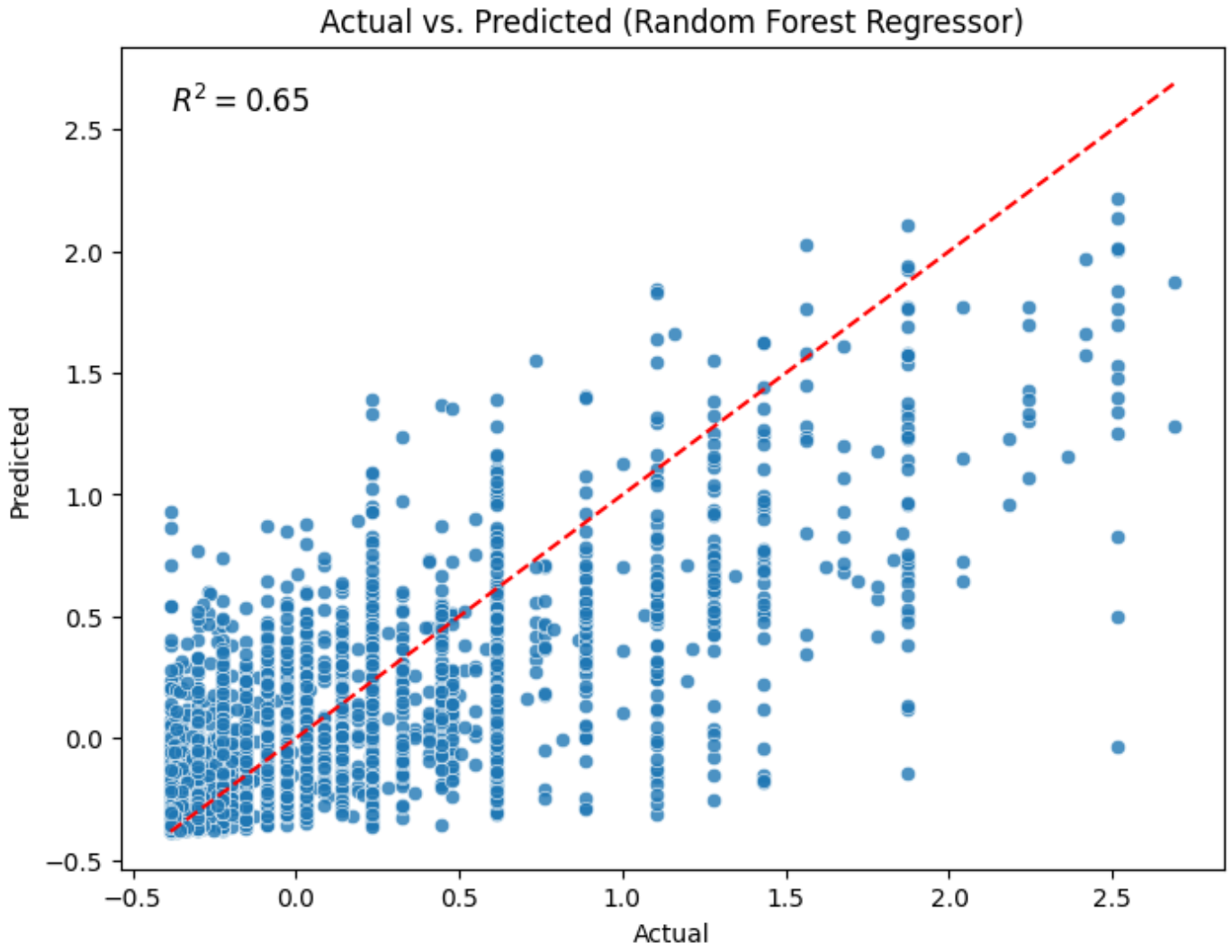
Random Forest Regressor

In [20]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV

# RandomForestRegressor with GridSearchCV
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
#Best parameters: {'max_depth': 30, 'min_samples_leaf': 4, 'min_samples_split': 10, 'n_e
rf = RandomForestRegressor(random_state=12)
grid_search_rf = GridSearchCV(rf, param_grid, cv=5, verbose=1, n_jobs=-1)
grid_search_rf.fit(X_train, y_train)

# Output the best parameters and the best score from the grid search
print("Best parameters:", grid_search_rf.best_params_)
print("Best cross-validation score: {:.2f}".format(grid_search_rf.best_score_))

# Fit the best model from the grid search
rf_best = grid_search_rf.best_estimator_
rf_best.fit(X_train, y_train)
y_pred_rf = rf_best.predict(X_test)

# Store best scores
r2_rf = rf_best.score(X_test, y_test)
```

```
mae_rf = mean_absolute_error(y_test, y_pred_rf)
mse_rf = mean_squared_error(y_test, y_pred_rf)

# Get results using helper function
print("---------RANDOM FOREST REGRESSOR----------")
print_results(r2_rf, mae_rf, mse_rf, rf_best.feature_importances_, rf_best.intercept_ if
plotRegression(y_pred_rf, r2_rf, 'Random Forest Regressor')
print("----------------------------------")
```

```
Fitting 5 folds for each of 108 candidates, totalling 540 fits
Best parameters: {'max_depth': 30, 'min_samples_leaf': 4, 'min_samples_split': 10, 'n_es
timators': 300}
Best cross-validation score: 0.62
---------RANDOM FOREST REGRESSOR----------
R-squared score: 0.6498
Mean Absolute Error: 0.13908100480770472
Mean Squared Error: 0.0636864290950335
Coefficients: [0.02638279 0.0141822  0.00337918 0.0004981  0.09077129 0.07939057
 0.00592247 0.00727853 0.00955331 0.01731108 0.02267189 0.00167844
 0.23794813 0.25821189 0.01933802 0.04249731 0.00406093 0.00608568
 0.00725488 0.01390497 0.00424855 0.00196571 0.02091952 0.00091304
 0.10363149]
Intercept: 0
```




```
----------------------------------
```

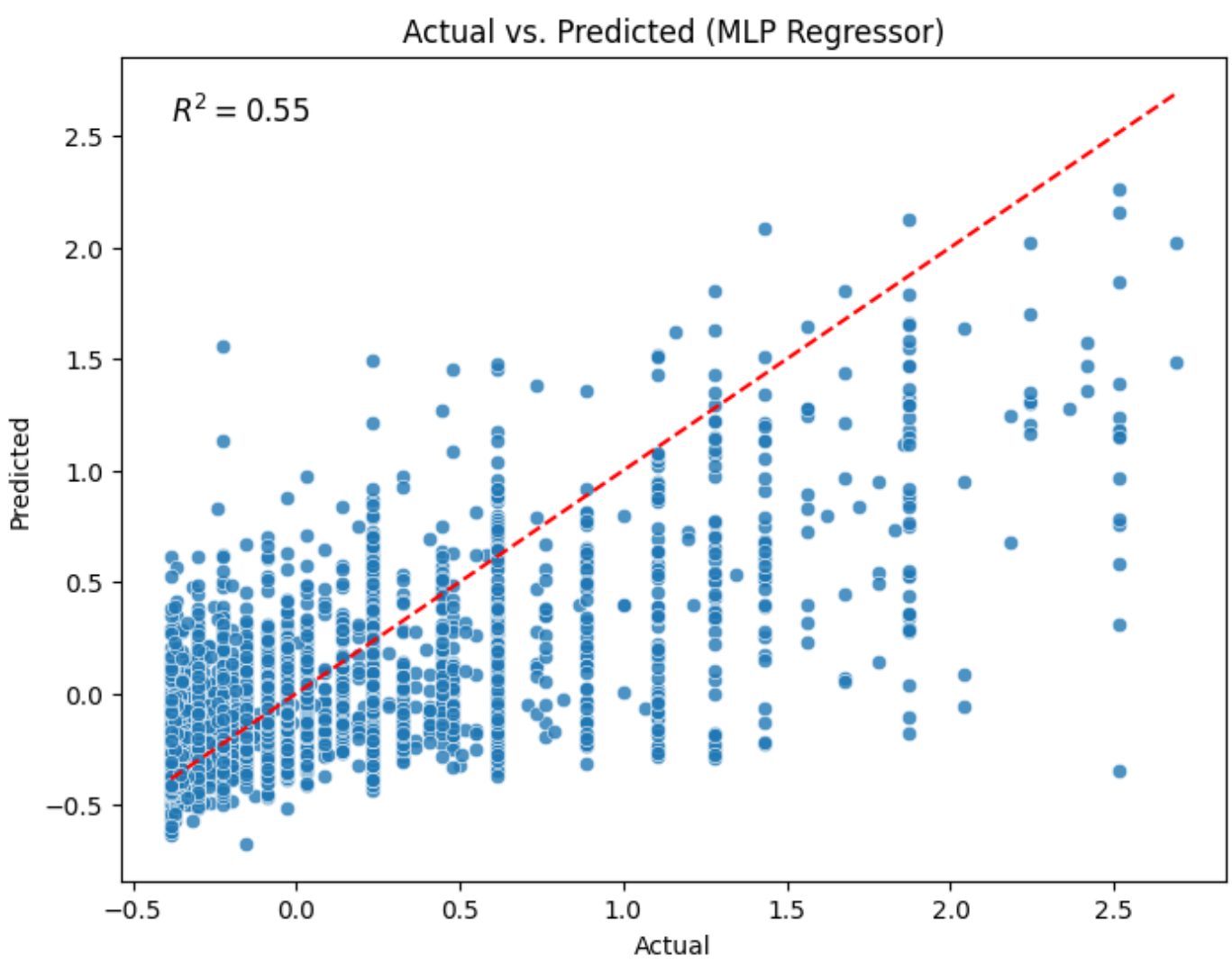
MLP REGRESSOR

In [22]:

```
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import matplotlib.pyplot as plt
```

```python
import seaborn as sns

mlp = MLPRegressor(random_state=12)

# MLP Regressor with GridSearchCV
param_grid = {
    'hidden_layer_sizes': [(100,), (50, 50), (100, 50), (50, 50, 50)],
    'activation': ['relu', 'tanh'],
    'alpha': [0.005, 0.01, 0.02],
    'learning_rate_init': [0.0005, 0.001, 0.005],
    'batch_size': [32, 64, 128],
    'early_stopping': [True],  # Early stopping enabled
    'validation_fraction': [0.1, 0.2],  # Different sizes of validation fraction
    'n_iter_no_change': [10]  # Number of iterations with no improvement
}
#{'activation': 'tanh', 'alpha': 0.01, 'batch_size': 32, 'early_stopping': True, 'hidden

grid_search = GridSearchCV(mlp, param_grid, cv=5, verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)

# Best model parameters from GridSearchCV
print("Best parameters:", grid_search.best_params_)
print("Best cross-validation score: {:.2f}".format(grid_search.best_score_))

# Using best parameters to fit MLPRegressor
mlp_best = grid_search.best_estimator_
mlp_best.fit(X_train, y_train)
y_pred_mlp = mlp_best.predict(X_test)

# Store best scores
r2_mlp = mlp_best.score(X_test, y_test)
mae_mlp = mean_absolute_error(y_test, y_pred_mlp)
mse_mlp = mean_squared_error(y_test, y_pred_mlp)

# Get results using helper function
print("---------MLP REGRESSOR----------")
print_results(r2_mlp, mae_mlp, mse_mlp, [], 0)
plotRegression(y_pred_mlp, r2_mlp, 'MLP Regressor')
print("-----------------------------------")
```

```
Fitting 5 folds for each of 432 candidates, totalling 2160 fits
Best parameters: {'activation': 'tanh', 'alpha': 0.01, 'batch_size': 32, 'early_stoppin
g': True, 'hidden_layer_sizes': (100, 50), 'learning_rate_init': 0.0005, 'n_iter_no_chan
ge': 10, 'validation_fraction': 0.2}
Best cross-validation score: 0.53
---------MLP REGRESSOR----------
R-squared score: 0.5492
Mean Absolute Error: 0.17074465634266245
Mean Squared Error: 0.08198398713080746
Coefficients: []
Intercept: 0
```

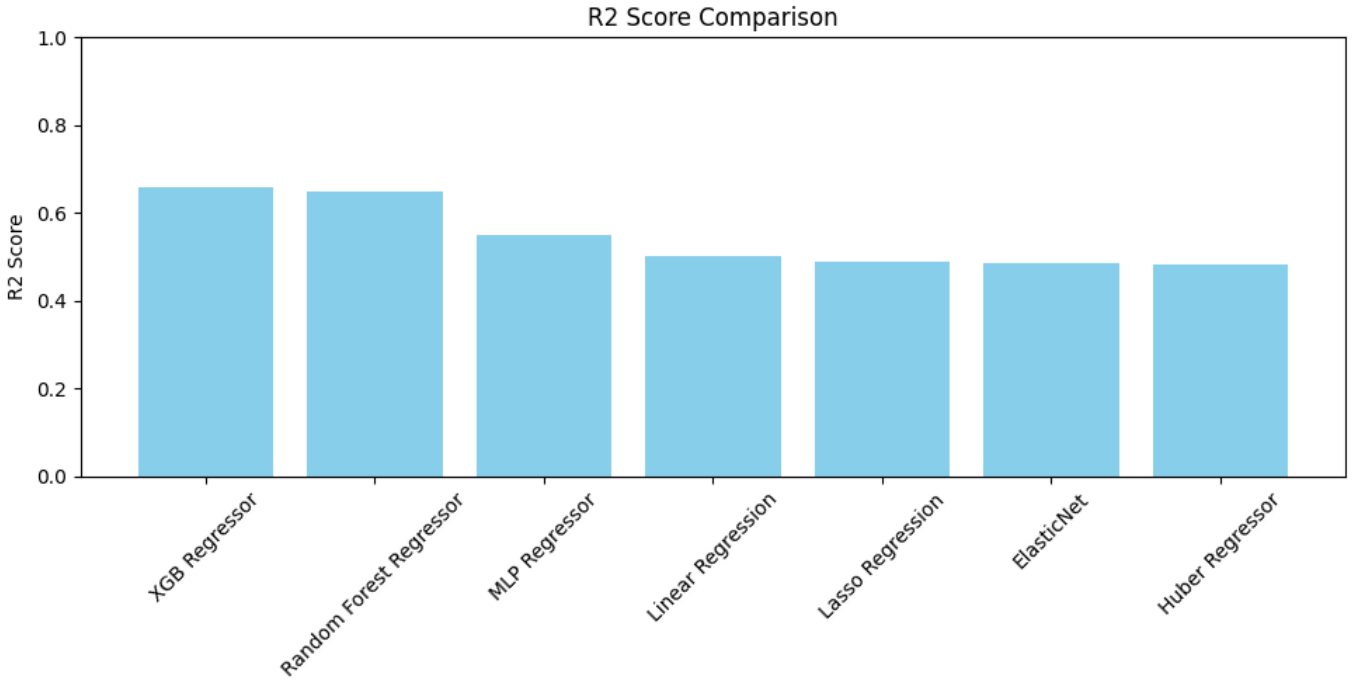


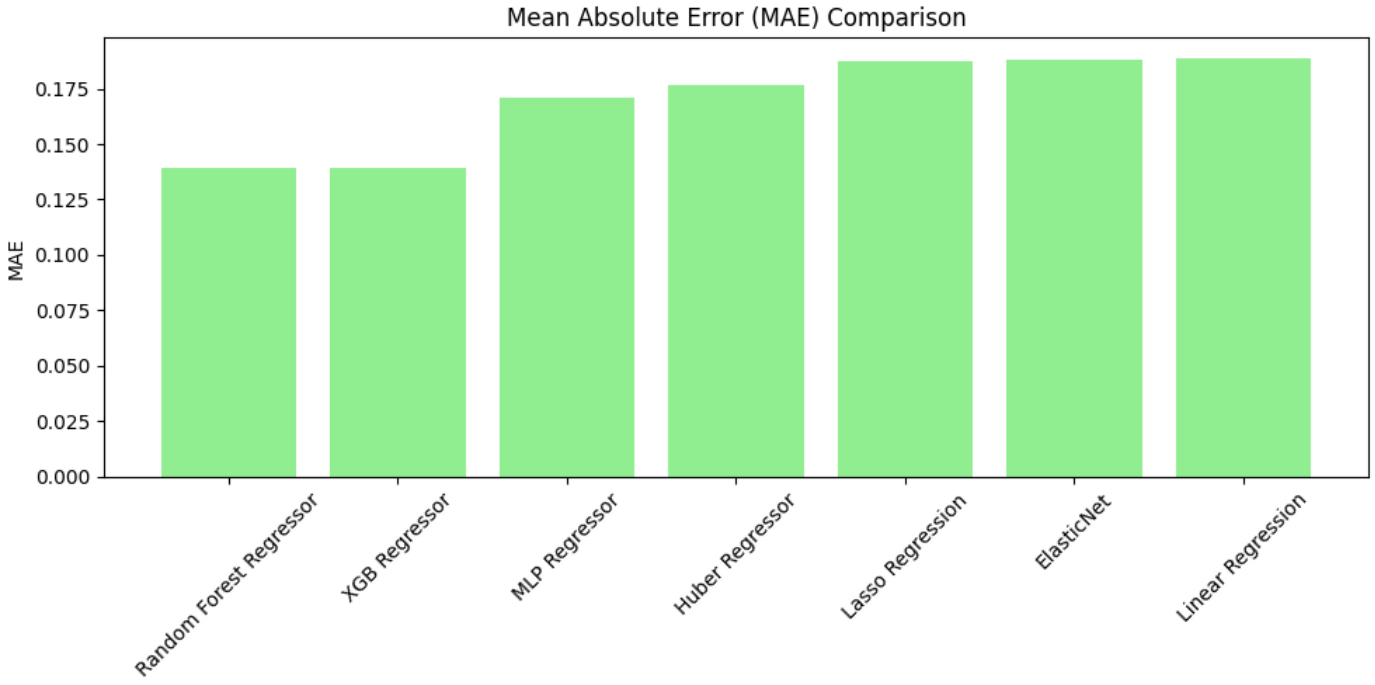
Model Evaluation Comparison

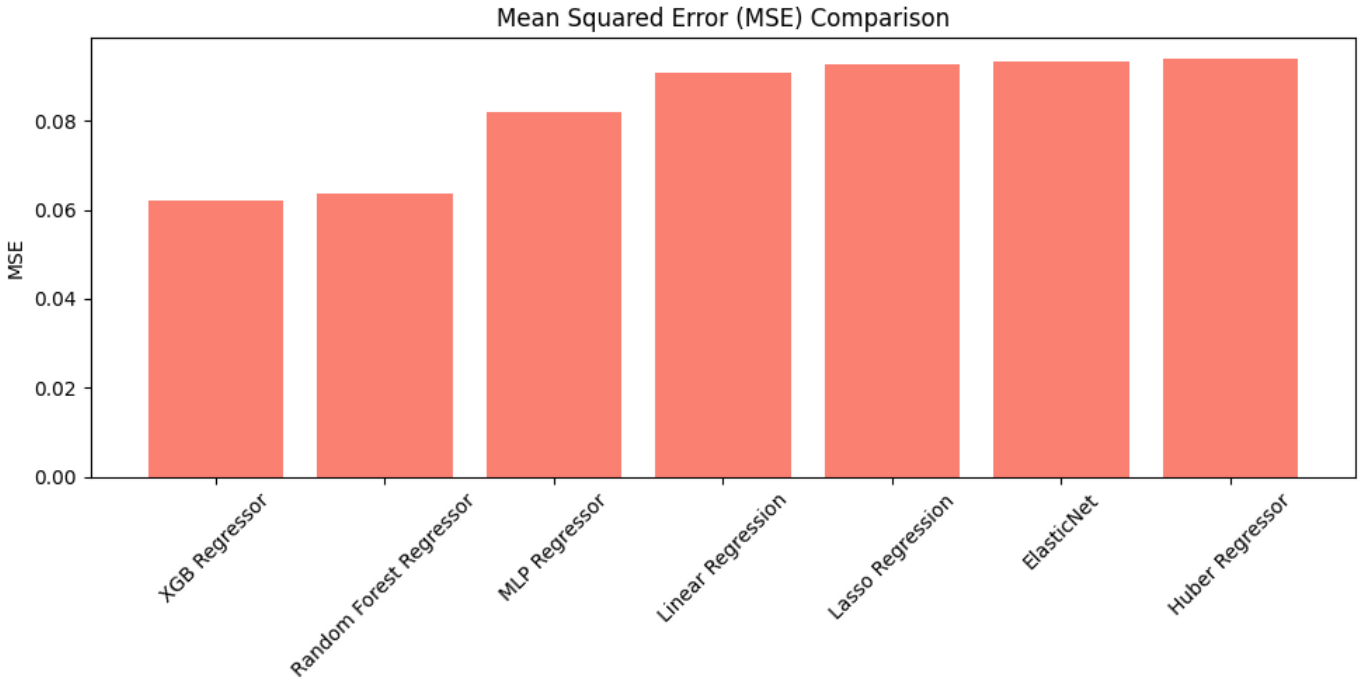
In [23]:

```
# Define model names and their evaluation metrics
models = [
    ("MLP Regressor", r2_mlp, mae_mlp, mse_mlp),
    ("Random Forest Regressor", r2_rf, mae_rf, mse_rf),
    ("Huber Regressor", r2_huber, mae_huber, mse_huber),
    ("XGB Regressor", xgb_r2, xgb_mae, xgb_mse),
    ("ElasticNet", r2_elastic_best, mae_elastic_best, mse_elastic_best),
    ("Lasso Regression", r2_lasso_best, mae_lasso_best, mse_lasso_best),
    ("Linear Regression", r2_lr, mae_lr, mse_lr)
]

# Create a DataFrame to store model names and metrics
results_df = pd.DataFrame(models, columns=["Model", "R2 Score", "MAE", "MSE"])

# Sort DataFrame by R2 Score (descending order)
results_df.sort_values(by="R2 Score", ascending=False, inplace=True)

# Plotting the comparison of R2 scores, MAE, and MSE
fig, axes = plt.subplots(nrows=3, ncols=1, figsize=(10, 15))

# Bar plot for R2 Score
axes[0].bar(results_df["Model"], results_df["R2 Score"], color='skyblue')
axes[0].set_title("R2 Score Comparison")
axes[0].set_ylabel("R2 Score")
axes[0].set_ylim(0, 1)
axes[0].tick_params(axis='x', rotation=45)
```

```python
# Sort DataFrame by MAE (ascending order)
results_df.sort_values(by="MAE", ascending=True, inplace=True)

# Bar plot for MAE
axes[1].bar(results_df["Model"], results_df["MAE"], color='lightgreen')
axes[1].set_title("Mean Absolute Error (MAE) Comparison")
axes[1].set_ylabel("MAE")
axes[1].tick_params(axis='x', rotation=45)

# Sort DataFrame by MSE (ascending order)
results_df.sort_values(by="MSE", ascending=True, inplace=True)

# Bar plot for MSE
axes[2].bar(results_df["Model"], results_df["MSE"], color='salmon')
axes[2].set_title("Mean Squared Error (MSE) Comparison")
axes[2].set_ylabel("MSE")
axes[2].tick_params(axis='x', rotation=45)

# Adjust layout to prevent overlap
plt.tight_layout()

# Show plot
plt.show()

# Display the sorted DataFrame
print("Sorted Results by R2 Score:")
results_df
```


R2 Score Comparison
R2 Score
1.0
0.8
0.6
0.4
0.2
0.0
XGB Regressor
Random Forest Regressor
MLP Regressor
Linear Regression
Lasso Regression
ElasticNet
Huber Regressor


Mean Absolute Error (MAE) Comparison
MAE
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
Random Forest Regressor
XGB Regressor
MLP Regressor
Huber Regressor
Lasso Regression
ElasticNet
Linear Regression


Mean Squared Error (MSE) Comparison
MSE
0.08
0.06
0.04
0.02
0.00
XGB Regressor
Random Forest Regressor
MLP Regressor
Linear Regression
Lasso Regression
ElasticNet
Huber Regressor

Sorted Results by R2 Score:

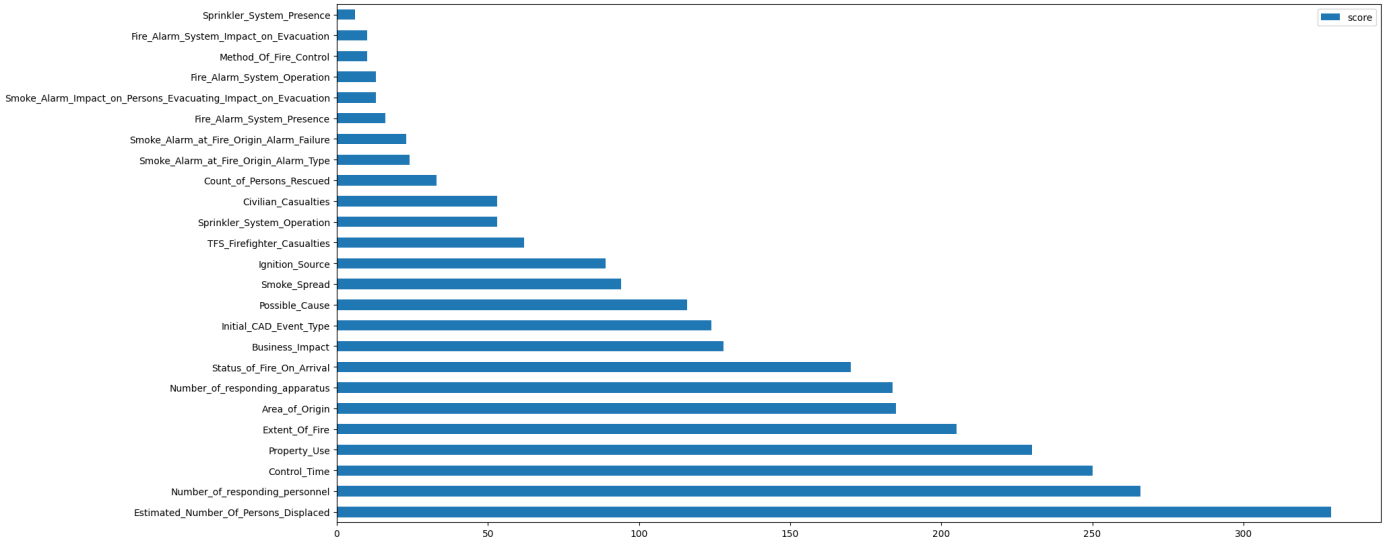
Out[23]:

	Model	R2 Score	MAE	MSE
3	XGB Regressor	0.658300	0.139514	0.062138
1	Random Forest Regressor	0.649787	0.139081	0.063686
0	MLP Regressor	0.549168	0.170745	0.081984
6	Linear Regression	0.500543	0.188554	0.090827
5	Lasso Regression	0.490150	0.187100	0.092716
4	ElasticNet	0.486042	0.187966	0.093463
2	Huber Regressor	0.483590	0.176682	0.093909

In [24]:
```
best_xgb_model = xgb_cv.best_estimator_  # Access the best XGBoost model from GridSearch

# Retrieve feature importance scores from the best XGBoost model
feature_importance = best_xgb_model.get_booster().get_score(importance_type='weight')

# Extract keys (feature names) and values (importance scores) from the feature importanc
keys = list(feature_importance.keys())
values = list(feature_importance.values())

# Create a DataFrame to visualize the top 40 features by importance
data = pd.DataFrame(data=values, index=keys, columns=["score"])
top_features = data.nlargest(40, columns="score")

# Plot the top 40 features by importance in a horizontal bar chart
top_features.plot(kind='barh', figsize=(20, 10))
```

Out[24]:

```
<Axes: >
```



Conclusion and Insights

Key Findings

Model Performance Overview:

- **XGB Regressor**
  - **R² Score:** 0.6583
    - 65.83% of the variance in the estimated dollar loss is explained by the model.
  - **MAE:** 0.139514

        - The average prediction error is approximately 0.14 units.
    - **MSE:** 0.062138
        - Smallest value among the models, indicating fewer large errors in its predictions.
- **Random Forest Regressor**
    - **R² Score:** 0.649787
        - Explains about 64.98% of the variance, which is slightly less effective than XGB.
    - **MAE:** 0.139081
    - **MSE:** 0.063686
- **Linear Regression**
    - **R² Score:** 0.500543
    - **MAE:** 0.188554
    - **MSE:** 0.090827
- **Lasso Regression**
    - **R² Score:** 0.490150
    - **MAE:** 0.187100
    - **MSE:** 0.092716
- **ElasticNet**
    - **R² Score:** 0.486042
    - **MAE:** 0.187966
    - **MSE:** 0.093463
- **Huber Regressor**
    - **R² Score:** 0.483590
    - **MAE:** 0.176682
    - **MSE:** 0.093909
- **MLP Regressor**
    - **R² Score:** 0.475081
        - The least effective model with a variance explanation at 47.51%.
    - **MAE:** 0.201347
        - Produces the largest average error.
    - **MSE:** 0.095457
        - Highest MSE, indicating potential large errors or overfitting.
- **Tree-based models (XGB and Random Forest)** are the most effective models that we tested, likely due to their ability to model complex and nonlinear relationships between predictors of estimated dollar loss in our data.

Feature Importance of XGB Regressor:

- **Top Features**
    - Estimated_Number_Of_Persons_Displaced
    - Number_of_responding_personnel
    - Control_Time
    - Property_Use
    - Extent_Of_Fire
    - Area_of_Origin

- Number_of_responding_apparatus
- Status_of_Fire_On_Arrival

These features seem to be the most important features in predicting estimated dollar losses. Based on this, the City of Toronto can more effectively allocate their resources. A simple example would be for property use. Depending on the type of property, different strategies can be set up to deal with fires. Another example would be for control time. As can be seen it is one of the top features, and hence the City of Toronto can deduct that they would need better training for their firefighters or to allocate more responding personnel for future fires if there needs to be an improvement in how effectively they mitigate economic losses.

Implications

Our two best performers are the XGB Regressor and the Random Forest Regressor. However, the implications of our results means that the model that we will choose is the XGB Regressor, even if its MAE is slightly worst compared to Random Forest Regressor, it has a better R^2 score and MSE.

This can help the City of Toronto to create an improved risk management plan through more informed decisions as our model can help them determine the features that are the most important when determining financial loss linked to fire incidents. It can also help the City of Toronto in terms of resource allocation and management in order to mitigate losses. Ultimately, our model will help in maintaining a higher quality of life for the people of Toronto by limiting economic losses and casualties that are usually associated with fire incidents.